An Automated Model for the Assessment of QoE of Adaptive Video Streaming Over Wireless Networks

Miran Taha[1, 2]; Aree Ali[1,4], Jaime Lloret[2]; Paulo R.L. Gondim[2,3]; Alejandro Canovas[2]
[1]Department of Computer Science, University of Sulaimani, Iraq
[2]Integrated Management Coastal Research Institute, Universitat Politécnica de Valencia, Spain
[3]University of Brasilia, Brasilia- Brazil
[4]Computer department, college of Science, University of Halabja, Iraq

miran.abdullah@univsul.edu.iq; aree.ali@univsul.edu.iq; jlloret@dcom.upv.es; pgondim@unb.br, alcasol@upvnet.upv.es;

Corresponding author: Jaime Lloret

Abstract
Nowadays, heterogeneous devices are widely utilizing Hypertext Transfer Protocol (HTTP) to transfer the data. Furthermore, HTTP adaptive video streaming (HAS) technology transmits the video data over wired and wireless networks. In adaptive technology services, a client's application receives a streaming video through the adaptation of its quality to the network condition. However, such a technology has increased the demand for Quality of Experience (QoE) in terms of prediction and assessment. It can also cause a challenging behavior regarding subjective and objective QoE evaluations of HTTP adaptive video over time since each Quality of Service (QoS) parameter affects the QoE of end-users separately. This paper introduces a methodology design for the evaluation of subjective QoE in adaptive video streaming over wireless networks. Besides, some parameters are considered such as video characteristics, segment length, initial delay, switch strategy, stalls, as well as QoS parameters. The experiment's evaluation demonstrated that objective metrics can be mapped to the most significant subjective parameters for user's experience. The automated model could function to demonstrate the importance of correlation for network behaviors' parameters. Consequently, it directly influences the satisfaction of the end-user's perceptual quality. In comparison with other recent related works, the model provided a positive Pearson Correlation value. Simulated results give a better performance between objective Structural Similarity (SSIM) and subjective Mean Opinion Score (MOS) evaluation metrics for all video test samples.

Keywords: HTTP Adaptive Streaming, Correlation Coefficient, QoE, QoS, and Subjective methodology

1. Introduction
Multimedia streaming services - particularly live video streaming and video on demand (VOD) - have become a widespread service for Internet Protocol (IP). IP video data traffic and streaming services have massively increased. IP video traffic is estimated to be 82% of all Internet traffic consumers by 2021, and live video streaming will account for 13% of Internet video traffic by the

same year, according to the Cisco Visual Networking Index (VNI) and global mobile data traffic forecast [1].

1.1 Motivation and Incitement

HTTP adaptive streaming (HAS) technology takes features of the HTTP protocol for video streaming. HTTP is applied for the transfer of video data as a primary protocol, since it is easy to configure and normally not blocked by firewalls or Network Address Translation (NAT) boxes. Netflix, Hulu, and YouTube, as commercial vendors, are familiarized with HAS technology to provide a better quality of adapted videos to end-users, subject to bounded Quality of Services (QoS), considering parameters like throughput, delay, packet loss, and jitter [2]. Furthermore, HAS often takes into consideration the role of involved parameters, which strongly affects the perceptual QoE. Several manufacturers implement their adaptive streaming (e.g., Apple (HLS), Microsoft (MSS), Adobe (HDS)), and most of them use the same mechanisms for adaptive streaming, while different characteristics and formats are applied [2, 3, 4]. The assessment of the adaptive multimedia streaming quality is of great interest to telecommunications companies that aim to increase quality expectations providing the adaptable video quality with network conditions to end-users. Although research has focused on adaptive video streaming, the validation of subjective and objective QoE performance models still demands research efforts. Several studies lack descriptions of QoE evaluation for adaptive video streaming. Thus, in terms of network parameters, some researchers have addressed only the bandwidth parameter to evaluate the QoE of HTTP adaptive streaming. Whereas other QoS parameters included delay, packet loss, and jitter [5]. Guan-Ming Su et al [6] indicated several research gaps and challenges for the assessment of video streaming QoE over wireless networks. The evolution of such networks from 3G to 5G and the rapid increase in the number of end-users have demanded higher quality of video streaming, which, together with real-time multimedia communication, have motivated the development of novel techniques. Part of such investigations involves optimization of multimedia streaming frameworks. Furthermore, the use of cutting-edge methods, e.g., Limelight Edge Functions, which has no server platform computation optimized for streaming video. It can also improve the streaming service for mobile network service providers.

1.2 Contribution

This paper introduces a methodology design for the QoE assessment of adaptive video streaming over wireless networks. Several parameters of the objective evaluation are taken into consideration for the design of an optimized subjective evaluation.

1.3 Paper Organization

The remainder of the article is organized as follows: Section 2 addresses a survey of related work and the state-of-the-art of subjective and objective evaluations of HTTP adaptive streaming over wireless networks; Section 3 provides the background of the influence factor on QoE; Section 4 describes the methodology for the subjective experiment assessment; Section 5 introduces the automated model; Section 6 focuses on the objective experimental parameters and evaluation results; Section 7 is devoted to correlations between QoS and subjective and objective QoE; finally, Section 8 provides the conclusions.

2. Related work

This section provides a detailed review of the factors which affect the QoE of HTTP adaptive streaming end-users and discusses some related work on the assessment in wireless networks. The QoE assessment model employs objective and subjective parameters to measure the video streaming quality evaluated by end-users. Such a quality can also be measured with the use of involved parameters such as bitrate, smoothness playback, and video quality Peak Signal-to-Noise Ratio (PSNR) [6], and the QoE of real-time video streaming can be improved by interference shaping [7]. A tunable bitrate model is required for the analysis of the dynamic adaptive video streaming QoE [8]. An alternative method, however, is the application of self-learning HTTP by the clients. A self-learning HAS client dynamically adjusts its performance interacting with the network environment for improving the QoE perceived [9]. Studies of the subjective score and objective evaluation of the wireless video perceptual quality highly impact the design and adaptation of wireless video streaming systems. Several evaluation schemes for objective video quality have been developed towards assessing human perceptual quality. Nevertheless, a subjective assessment of a video quality database does not significantly reflect degradations found by actual encoders-decoders and wireless channel generation [10]. Recently, an efficient QoE-Aware-based algorithm was proposed for HAS video delivery in heterogeneous wireless networks due to the increased consumption of video content by smart mobile users. Since the mobile network scope cannot be expanded as fast as required, a smart scheduler that efficiently allocates requested resources and provides high QoE to most users must be developed [11].

From the user's point of view, QoE and QoS are closely related. However, the relation among their parameters, such as coding, decoding, and network parameters, cannot be easily mapped, especially for the video-on-demand service. In general, QoE can be obtained from subjective and objective evaluation metrics in either laboratory-based test experiments or simulated-based ones. Towards avoiding high-cost tests based on laboratory experiments, objective quality models must predict QoE based on objective QoS parameters. Moreover, the increasing demand for video streaming over the Internet requires new approaches (e.g., data-driven QoE models) for the processing of massive data [12, 13, 14]. Poojary S. et al [15] developed a system that analyzes QoE for adaptive video streaming over wireless networks. They studied a dynamic system based on random arrivals and departures for different classes of users through standard Dynamic Adaptive Streaming over HTTP. A Markov chain-based analysis calculates QoE from a user's point of view, i.e., starvation probability, anticipated delay, the average quality of the video, and switching rate. The user's QoE was improved by an adaptive client-based scheme that enables efficient use of wireless networks. In [16], the authors introduced a new method in multimedia streaming services that employs Adaptive Media Playout (AMP) for real-time QoE monitoring systems. Their approach was implemented in VideoLAN Client (VLC) media player according to the client's buffer fullness of the client's that regulates the playout rate of videos more efficiently. However, the authors conducted a significant number of experiments over wired/wireless video streaming towards improving the performances of QoE monitoring systems. They carefully considered enhancing the AMP of QoE of video streaming services regarding Mean Opinion Score (MOS). Huawei Mlab [18] proposed a Video Mean Opinion Score (vMOS) as a new QoE measurement standard of video performance in a mobile environment for video streaming over mobile networks. Nevertheless, few studies on vMOS quantity-based have considered the relationship between vMOS and QoS parameters. Such an issue has been addressed through the development of a new data framework based on video streaming QoE analysis that uses K-means clustering and logistic regression. According to intensive experiments on real datasets, the framework proposed in [17] surpassed the prediction accuracy of other methods. Another way to improve end users' video quality is to shift from traditional QoS video services to QoE-based video services delivery. Recent research has developed QoE models for HAS applications, currently used by most video streaming services, such as Netflix and YouTube. A complete review of works in the area of QoE modeling based on influence factors and subjective test strategies is provided in [19, 21, 28, 29, 32, 36]. Presently, Internet traffic is dominated by video streaming applications. Particularly, (HAS) has emerged as a forceful standard for video streaming over best-effort Internet is to improve the quality perceived by the users' QoE. The main common factor that affects the users' QoE is video play out in wireless environments. Which can cause a quality degradation in live events.

Several studies have attempted to overcome the problem of freezing video playout and optimize QoE from a user's perspective [20]. Barman N. et al [22, 27] presented two no-reference machine learning based on quality estimation models for gaming video streaming applications through bitrate resolution and temporal information. A small-cell network is an emerging solution for high video traffic. Nevertheless, it faces some basic problems, i.e., high backhaul cost, interference, and quality of experience (QoE). Towards overcoming them, Liu et al. [23] developed a collaborative strategy technique that provides a reliable video transmission in small-cell networks with caching. The authors employed encoding and segmentation for each video file with maximum distance separable rate-less code, and, subsequently, a part of the segment was cached at Small-cell Bases Stations (SBSs). A greedy algorithm successfully transmitted real-time video streams from the SBS to the users, thus minimizing video freeze (delay) and enhancing QoE. Several network-assisted streaming models have been analyzed, and depend on the collaboration between network infrastructures and video streaming applications. Objectively, a max-min fairness optimization issue is fixed at run-time, and performance parameters of QoE, such as Video Quality Fairness, video quality, and switching frequency are evaluated. Moreover, QoE and cost awareness have been managed for Content Delivery Networks (CDNs) and content transmissions over long distances [24, 25]. Schatz R, et al. [26] developed an approach of subjective QoE evaluation for omnidirectional video (OV) streaming. They studied the QoE influence of stalling in the OV streaming using head-mounted displays (HMDs). Their test results indicated that the subjective evaluation test for OV is significant.

Li Wenjing et al. [30] studied the roles of interactive users´ behaviors to evaluate video streaming quality. Since the QoE of HTTP for video streaming can be assessed under different circumstances concerning such behaviors, the authors analyzed those roles and considered the characteristics displayed when the users´ experiences matched their interactive behaviors. The backpropagation neural network (BPNN) validated the model, and, according to the simulation results, the effects of user´s interaction behaviors and their influences on the QoE of adaptive video streaming were analyzed [30].

The effect of network´s QoS on user´s QoE for a mobile video streaming service using H.265/VP9 codec was investigated in [31], and an algorithm based on QoE aware association for 5G Heterogeneous Networks was proposed in [33]. Toshiro Nunome and Hiroaki Tani [42] developed an assessment multidimensional QoE of HTTP-based streaming in seeking operation to assess the influence of two transmission methods, namely progressive download, and adaptive bitrate streaming. A subjective experiment under several network load conditions and two contents revealed the adaptive bitrate streaming was not necessarily effective for QoE enhancement, since the effectiveness of the method depended mainly on the use of both system and network conditions. T. Nunome and K. Mizutani proposed a system that used Leader-Based Protocol (LBP) and Auto Rate Fallback (ARF) to evaluate the QoE of multimedia streaming over Wireless networks employing mechanisms of reliable group cast and rate-adaptation. The results show the joint method enhanced QoE when the wireless channel was under distortion conditions [43]. Two studies [42 and 43] focused mainly on improvements in-network services towards enhancing QoE, whereas our system is based on an automated model for evaluating subjective and objective adaptive video streaming. After identifying the importance of video QoE assessment for network operators, the International Telecommunications Union (ITU) has developed a model for MOS prediction, namely ITU-T P.1203 for adaptive video streaming, which estimates MOS applying only QoS parameters. It is based on subjective QoE ratings obtained from experiments with real participants, as well as on a parametric model for audio-visual quality assessment of adaptive video streaming. It consists of three main blocks that involve a video quality estimation module (Pv), an audio quality estimation module (Pa), and a quality integration module (Pq) comprised of modules for audio/video temporal integration and estimation of the impact of stalling [44]. Video Multi-method Assessment Fusion (VMAF) and QoE-aware DASH (QDASH) are very interesting systems for the evaluation of the QoE of adaptive video streaming. VMAF, an emergent full-reference objective video quality assessment model developed by Netflix, is particularly used for assessments of video streaming services [45], and QDASH improves the user-perceived quality of video watching. DASH enhances the QoE for users by automatically switching quality levels according to a network´s conditions [46]. The authors observed the available bandwidth method eases the selection of video quality levels and assessed the QoE of quality transitions through subjective experiments. Finally, they integrated both QoE-aware quality adaptation and network measurement into a more complete DASH system.

This paper addresses the evaluation of the QoE based on QoS metrics such as bandwidth, delay, and packet loss. A statistical model based on the Pearson correlation coefficient is used because of the normal distribution behavior of the streaming data and for showing the correlation between subjective and objective quality measurements.

3. Factors that influence QoE

Several factors can influence the QoE of a video. Although the behavior of wireless network parameters is degraded, it can produce factors that influence the end user's perceptual quality of HTTP adaptive streaming. Such factors are classified into three categories, namely initial delay, quality switch, and stall frame. The segment length is one of the video characteristics in HTTP adaptive streaming. A video includes several qualities, and each quality includes a series of segments, whose length is measured in seconds. However, the segment size changes the function of the size of the I-Frame and complementary frames such as B-frames and P-frames.

This study provides a methodology based on the effect of different parameters on the QoE in HTTP adaptive streaming service and developed through the following steps:

- The specification of optimum initial delays when users start representing the different segment lengths of a video.
- The initial delay is always present in multimedia streaming services since a certain amount of data must be transferred before decoding and playback. The practical value of the minimal achievable initial delay depends on the rate of available transmission data and encoder settings.

The video playback delay is usually higher than technically necessary, towards filling the playout buffer with a larger amount of video playtime in the receiver. Playout buffer is an efficient tool for tackling short-term throughput variations. However, the amount of initially buffered playtime must be compromised between the actual segment length of the corresponding delay (i.e., if the segment length is longer, more buffered playtime is needed and a longer initial delay is required). The risk of buffer depletion might happen.

- Detection of the effect of abrupt switches and smooth switches on QoE according to video quality. Smooth switching performs only slightly better than abrupt switching.
- Detection of the effect of frames stall included, stall at the low-level video quality, and stalls in each quality switch. A stall becomes clear when the user visualizes a spinning wheel icon, which generally appears when the buffer is emptied before the end of the current video chunk segment, thus interrupting playback until further video segments are loaded in the buffer.
- QoE assessment in the wireless scenario. [6, 7, 12, 34, 35] focused merely on bandwidth parameter to find the assessment of QoE for HTTP adaptive streaming. HTTP uses TCP, however, other QoS parameters (e.g., delay and packet loss) are also affected the performance, to address this limitation of existing models we develop an automated streaming model based on more parameters, namely (delay and packet loss).
- The assessment of the QoE of HTTP adaptive streaming over heterogeneous devices, such as PC, mobile, and TV.

4. Experiment for subjective assessment

The most reliable way to determine the video quality is a subjective assessment. To follow different real-life network scenarios, a special attempt for designing the experiments is taken into consideration, which included the choice of test methodology and evaluation methodology in order to assess the service application of HTTP adaptive video streaming by a human. The experimental setups are described in detail as follows.

4.1 Test Methodology

In this section, the requirements for the experimental tests are described. In subsection 4.1.1, different scenarios are considered for almost all users (at home, pedestrians, and others) while in 4.1.2, test materials are presented for several video sequence qualities. Moreover, in subsection 4.1.3, (34) observers (28 males and 6 females) were selected for the tests towards reliable results to evaluate the subjective quality of videos. Finally, in 4.1.4 data processing is performed to remove unwanted participants.

4.1.1 Scenario of the tests

An adaptive video streaming service that consumes video sequences over heterogeneous devices, including PC, TV, laptop, and smart device or mobiles (See Figure 1), was provided towards real-life scenarios and end-users´ satisfaction. Nevertheless, they accessed the multimedia service provider through separate connection points within a network (e.g., cable connection, wireless network connection, or cellular network). IEEE 802.11 was employed for nearly all users (home view, pedestrians on a university campus, and others) to receive the adaptive streaming of multimedia services over wireless networks. Such scenarios were considered for regular tests and study of the dataset obtained, and their topologies included a stable condition, under which users consumed video services at home through devices, such as TV, laptop, or mobiles. Later, users consumed the services under a mobility condition, i.e., as pedestrians. Therefore, real testbed setup and configuration were provided, which included: NGINX web server is used as a main server and DASH web service application hosted on it. The encoding of the raw video data and adaptive streaming is done by the server. A Network traffic shaper, which is a hardware device equipped with Linux Operating System (Ubuntu), was employed. It can shape QoS parameters available for upstreaming and down streaming using priority mechanisms for network resources and guarantees definite bandwidth depending on predefined policy rules. It can also use concepts of traffic classification, QoS, policy rules, and queuing disciplines. This classification controls and shapes uplink, downlink of the network, jitter, packet loss rates, and delay. Furthermore, a script file that runs on the traffic shaper device is created for automatically shaping the network parameters when clients start to watch a video. Throughput, delay, and packets are separately shaped according to real scenarios. A network monitor system is based on Ubuntu operating system, equipped with open-source web tool network monitoring. The monitoring approach enabled the extraction of network information through the monitoring of the HTTP request between client and server; therefore, the network tool analyzed the performance of the captured TCP and established a correlation between each QoS parameters, such as bandwidth, delay and packet loss, on the performance of the packets transfer between server and clients. When a client starts to play a streamed video, an automated log file is produced in the client's device, the file has information on the video, such as real time of the computer, video time, startup delay, stall times and duration, video bitrates in kbps, and quality representation, denoted by $Q_{i,i}$and the quality resolution may 4k, 2k, etc.

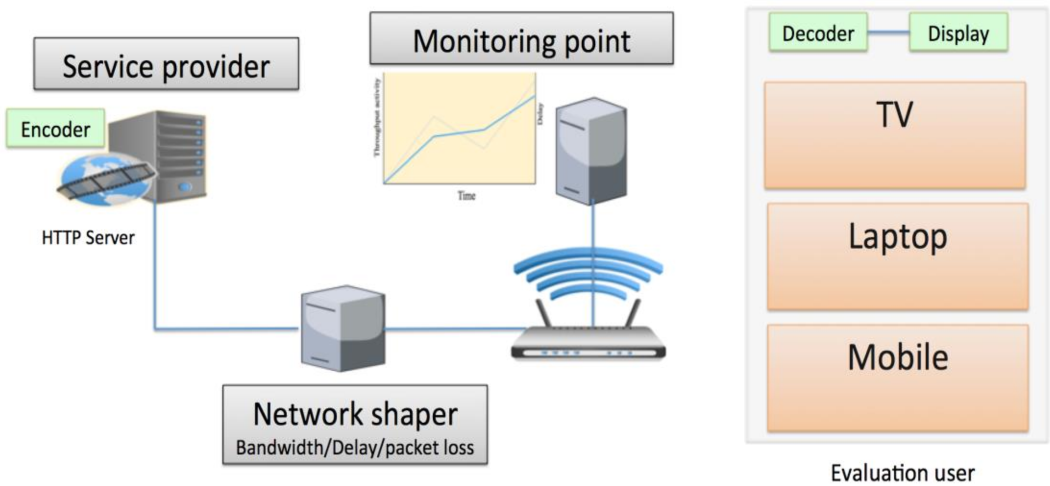


Fig.1. The subjecitve assessment testbed.

4.1.2 Test Materials

Table 1 shows several video sequences that covered sufficient targets of real-world media and applications. Such targets can lead to considerable degradation during a quality evaluation. Three minutes (180 seconds) from each selected video were encoded towards an accurate evaluation. This video length was chosen for generating the largest number of segments and enabling a better evaluation from users' points of view. The only drawback of the use of long sequence time is the participants´ fatigue. Short sequences can provide inaccurate results.

Four types of videos with different characteristics were chosen (see Table 1 and Figure 2), and their quality resolutions were 4k, HD, and SD. Every video was separately encoded with x.264 into six representations, so that diverse quality levels could be covered (see Table 2). The selection of bitrate levels was based on recommended Netflix [2]. GPAC's MP4Box segmented the test sequences into 1, 2,4,6,8,10,15,30 second lengths. For providing different network profiles variable throughput of the network was used for the first case, and the network emulator then set the delay parameters in milliseconds, according to the observation within a long-distance line connection range. Such a representation leads to a wide range of applications with real-life scenarios. Each QoS parameter is traced by a network tracer, totaling 12 tracers, they represent stationary and different mobility scenarios, such as the train, the pedestrian, the car, among others. The average network bandwidth ranged between 300 Kbps and 20 Mbps, thus assuring the coverage of all bitrate ranges in the bitrate step.

Code	**Genre**	**FPS**	**Characterization**
1	Tears of Steel	30	High motion fast changing the relatively dark scenes; high disparity
2	Sport Football	30	Soccer; average motion; wide-angle camera sequence with uniform camera panning medium disparity
3	Star War Video	30 60	Sudden motion High motion fast changing the relatively Dark and White scenes; high disparity
4	Big Buck Bunny Cartoon	30 60	Smooth motion of objects is dominant; static background; very ow disparity

Table 1. Characteristic of the sequences.

Fig.2. Snapshot of the video sequences.

Table 2. HAS representations for the test sequence.

Quality level code	**Resolution**	**Aspect**	**Bitrate (Kbps)**
1	384 x 288	SD	300
2	512 x 384	SD	700
3	1280 x 720	HD	1500
4	1920 x 1080	HD	6000
5	2048 x 1440	2K	11658
6	3840 x 2160	4K	19684

4.1.3 Methodology of subjective evaluation

According to ITU-T Rec. P.911-ITU-T Rec. P.911: Subjective audiovisual quality assessment methods for multimedia applications [49], the possible number of subjective evaluations in tests (as well as in usability tests on terminals or services) ranges from 4 to 40 participants. Four is the absolute minimum for statistical reasons, while a point is rarely found above 40. 34 observers (28 males and 6 females) were chosen for our test scenarios towards the achievement of reliable results. They were non-experts (naïve users), i.e., they were not directly concerned with television picture quality as part of their normal work. All of them had correct-to-normal sight, and information, such as name, occupation, gender, and age were taken. Their ages ranged from 20 to 45 years, thus averaging 25.

Absolute Category Rating (ACR) ITU-R [36] 5-point scale corresponding to the perceived quality was selected for the participants´ feedback (see Table 3). They rated the quality of streamed video in three levels, i.e., one for initial delays, another for quality switching (sharp and frequent switches), and one for stalling, and directly sent their feedback to a server database when the streaming of videos was finished.

Table3. Subjective evaluation method.

Session of streaming video	Vote	Vote sends to server

4.1.4 Data processing

According to the subject removal scheme suggested in [37], four participants were removed, thus totaling 30 valid participants. A linear rescaling of Z-scores was then required for the maintenance of the [1, 5] range (See Table 4). Then, for each individual video, the MOS has been calculated from all valid subjects which equivalents to the average rescaled Z-scores.

Table 4. The scale of subjective evaluation.

CODE	ACR
5	Excellent
4	Good
3	Fair
2	Poor
1	Bad

4.2 Result Analysis

The performance evaluation of the tests has found for different segment lengths, where the influence parameters of initial delay, quality switching, and video stalling are essential metrics that are impacted on the QoE in HTTP adaptive streaming. We investigated and used the observed values of “initial delay", "stalling" and "switching” according to reference [2] in Figure (5) and Table 1. For example, if the segment is 1s, the initial delay of the video playback is 1.01s, while for the 10s segment length, it is 10.3. Moreover, the stalling for 1s and 10s segment lengths are 5 and 2 times, respectively, and the switching video quality for 1s segment length is 4 times. Whereas for 10s, it is 1 time. Further, those values are changed under the impact of network conditions. Figures 3 and 4 depict the effect of each metric on the subjective evaluation. According to the figures, small segments are rerecorded with higher MOS than large segments for both the initial delay and video stalling. The users perceived the quality of videos from segments 1 to 8. However, the perceived quality degraded from 10 to 30 seconds, and users were no satisfied with the receiving of videos.

Our adaptation algorithm for video streaming chose the next predicted segment length. Apparently, the oscillation is high for small segment lengths, since the video buffering takes less time, and vice versa.

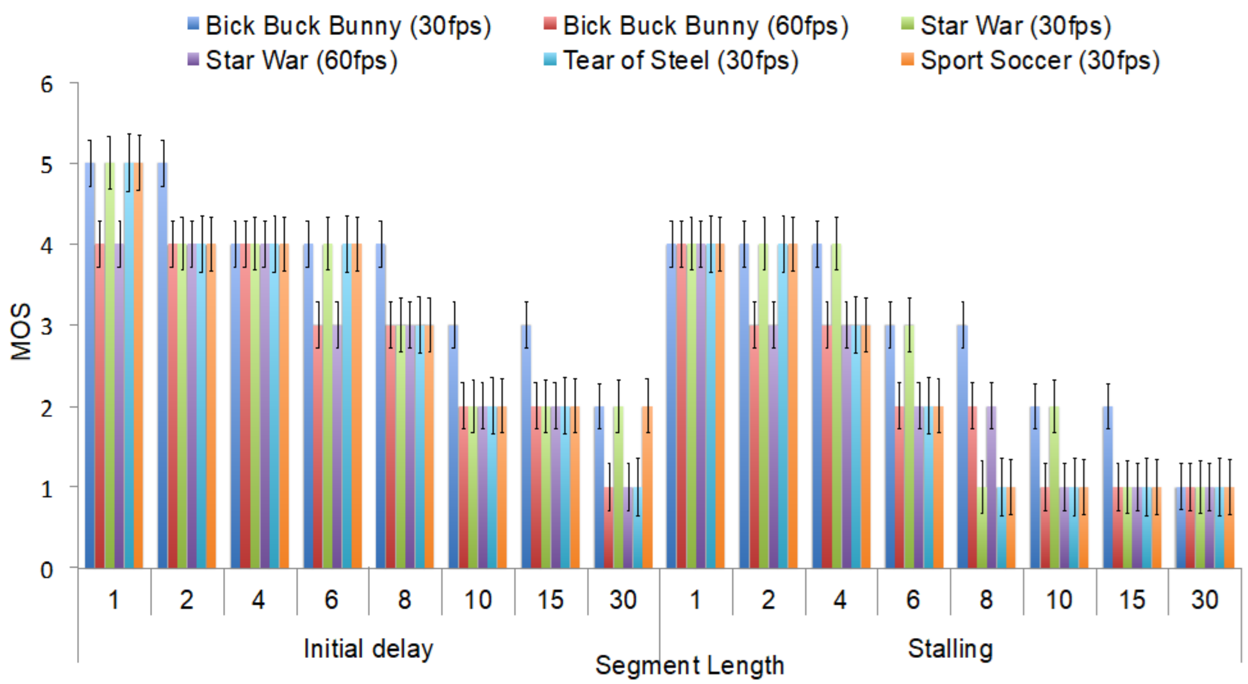


Fig. 3. QoE evaluation based on the initial delay and video stalling.

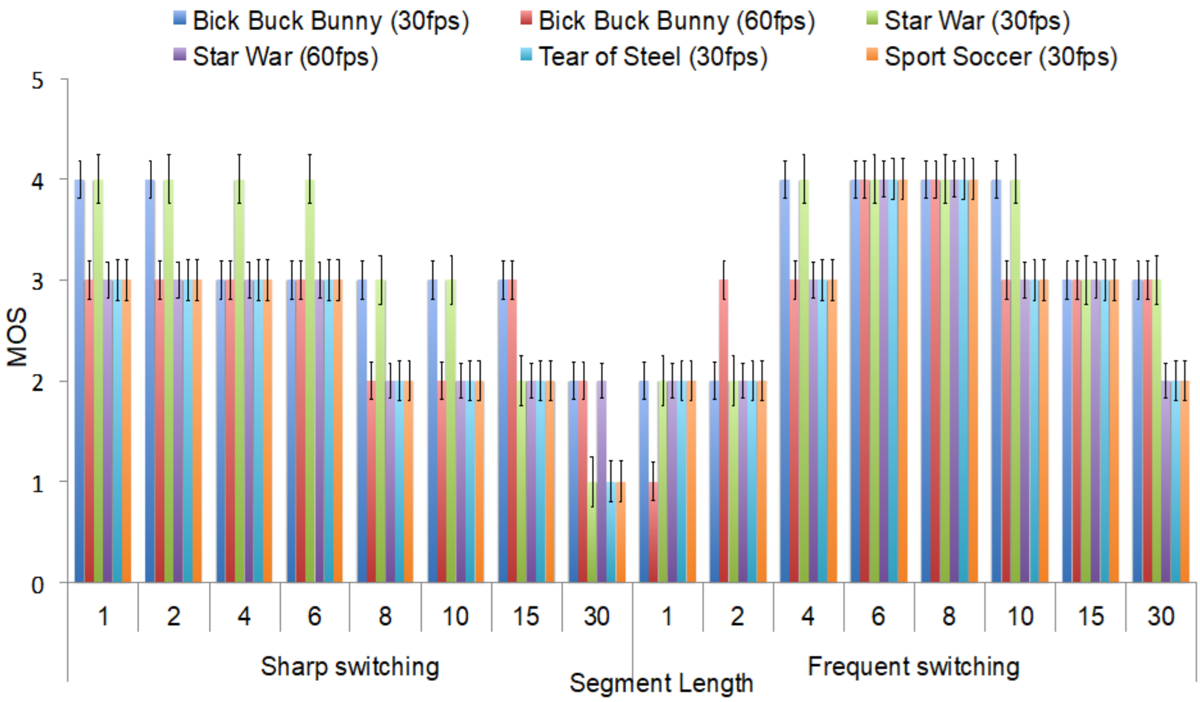


Fig. 4. QoE evaluation based on the quality oscillation.

According to Figure 4, the subjective evaluation was found for sharp switching and frequent switching. The evaluation of the video quality according to quality oscillation was changed due to the characteristics of adaptation login, network throughput, and videos. Frequent switches are very high when the chunk size is small. This is the buffer length that will not fill to display the video content on the device also sharp switches are high in large segments because the large segment has higher code efficiency and users can perceive high to the sharp switch from quality to another quality.

Therefore, we find the average subjective evaluation of all videos, according to the effective metrics on human eyes. Figure 5 shows the initial delay is very short in small segments; however, the MOS value is high. From 8 seconds to 30 seconds, the initial delay is very long and users can perceive the high annoyance of adaptive video streaming. Moreover, video stalling is long for 10, 15, and 30 segment lengths; the sharp switch is very long in small segments, and the recorded value for MOS is low, which annoys users.

Four types of sequences were selected for the evaluation of the adaptive video streaming performance in different devices. The video chunk size was 2 seconds, according to the proposed assessment methodology. The experiments were conducted in three types of devices, namely TV, Laptop, and mobiles [38]. Figure 6 shows the evaluation of subjective metric (MOS), the evaluation of the mobile device was recorded high result than that in laptop and TV. This is because users perceive fewer oscillations in the video quality in mobile devices, initial delay than other devices such as Laptop and TV; therefore, the characteristic of the video also change the evaluation results, as shown in the figure for high-motion videos, like Tear of steel and football match.

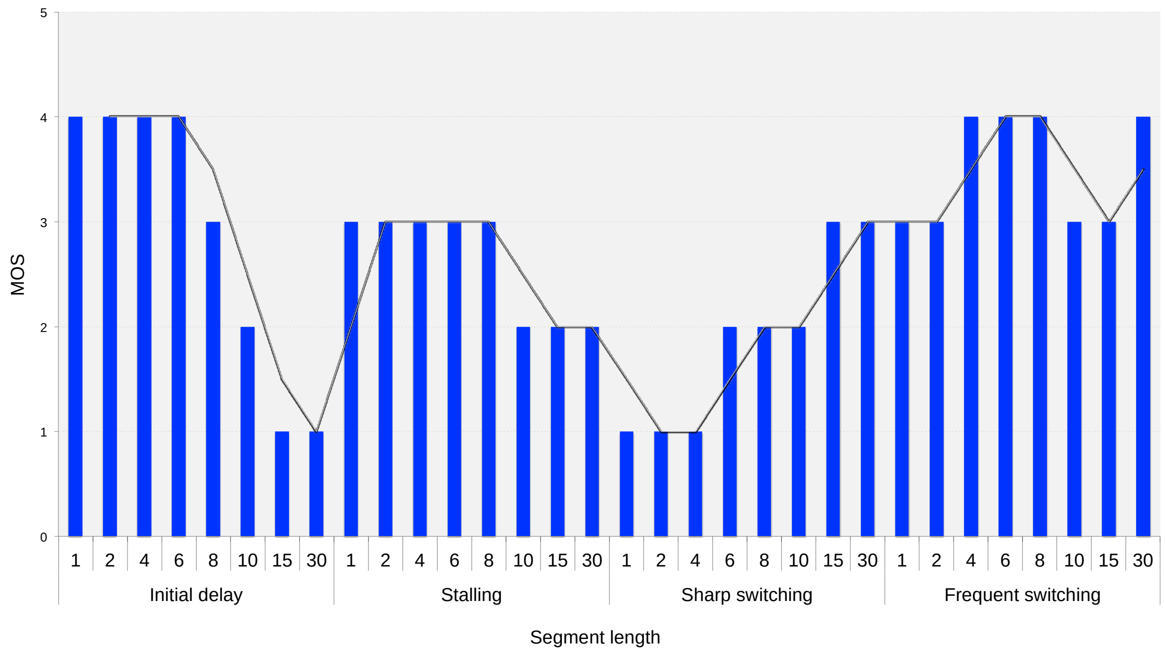


Fig. 5. Average subjective evaluation for all videos.

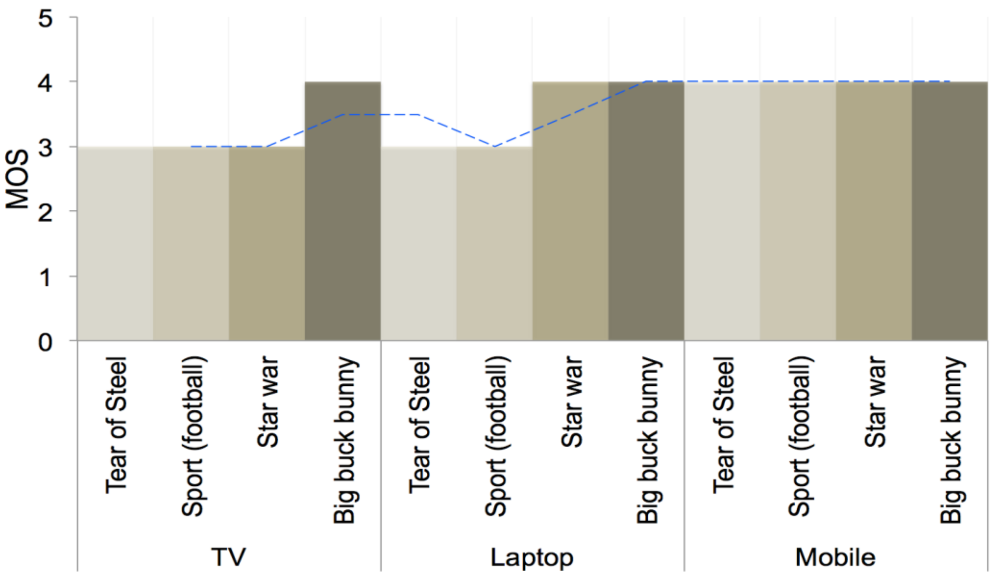


Fig. 6. QoE evaluation on different devices when segment length is 2 sec.

5. Automation model

In the HTTP adaptive video streaming, subjective and objective quality measurements are required for the evaluation of the reconstructed video. The transport quality (initial delay, sharp-frequent switches, and stalling) affects the QoE of the video for end users. We have developed an automated based model for systematic QoE evaluations which consists of video characteristics, segment length, QoS parameters, subjective QoE, objective QoE, and statistical correlation between QoS and QoE. Figure 7 illustrates the flowchart of the system.

The functional process steps are described as follows:

1. A raw video is encoded with different qualities (low and high).

2. An input video is segmented into different lengths (1 to 30 seconds).
3. The available bandwidth of the wireless network must be acquired. According to our adaptation algorithm, it is provided downloading the first segment of the streamed video.
4. An initial bitrate must be selected according to the quality of the video test sample (see Table 2). The selection is normally based on the video quality resolution – for SD videos, bitrate ranges from 300 to 700 Kbps, whereas for HD videos, it can reach 6000 Kbps.
5. The network bandwidth should always be greater than the initial video bitrate for ensuring end users´ satisfaction when watching a reconstructed video; otherwise, the quality of the video is degraded and perceptually not accepted.
6. The subjective QoE is determined by MOS method according to initial delay, the sharp-frequent switch, and stall duration.
7. The optimal value of MOS must be higher than 3 for preserving the quality of the video.
8. To get this satisfactory quality, the initial delay and stall duration should also be less than the selected segment length.
9. A larger segment size for sharp and frequent switches is necessary for reducing the effect of quality oscillation.
10. Finally, the system is trained with all the parameters and showed that in most cases, MOS must be greater than 3 to the satisfy client's requirements regarding the quality reconstruction of the video.

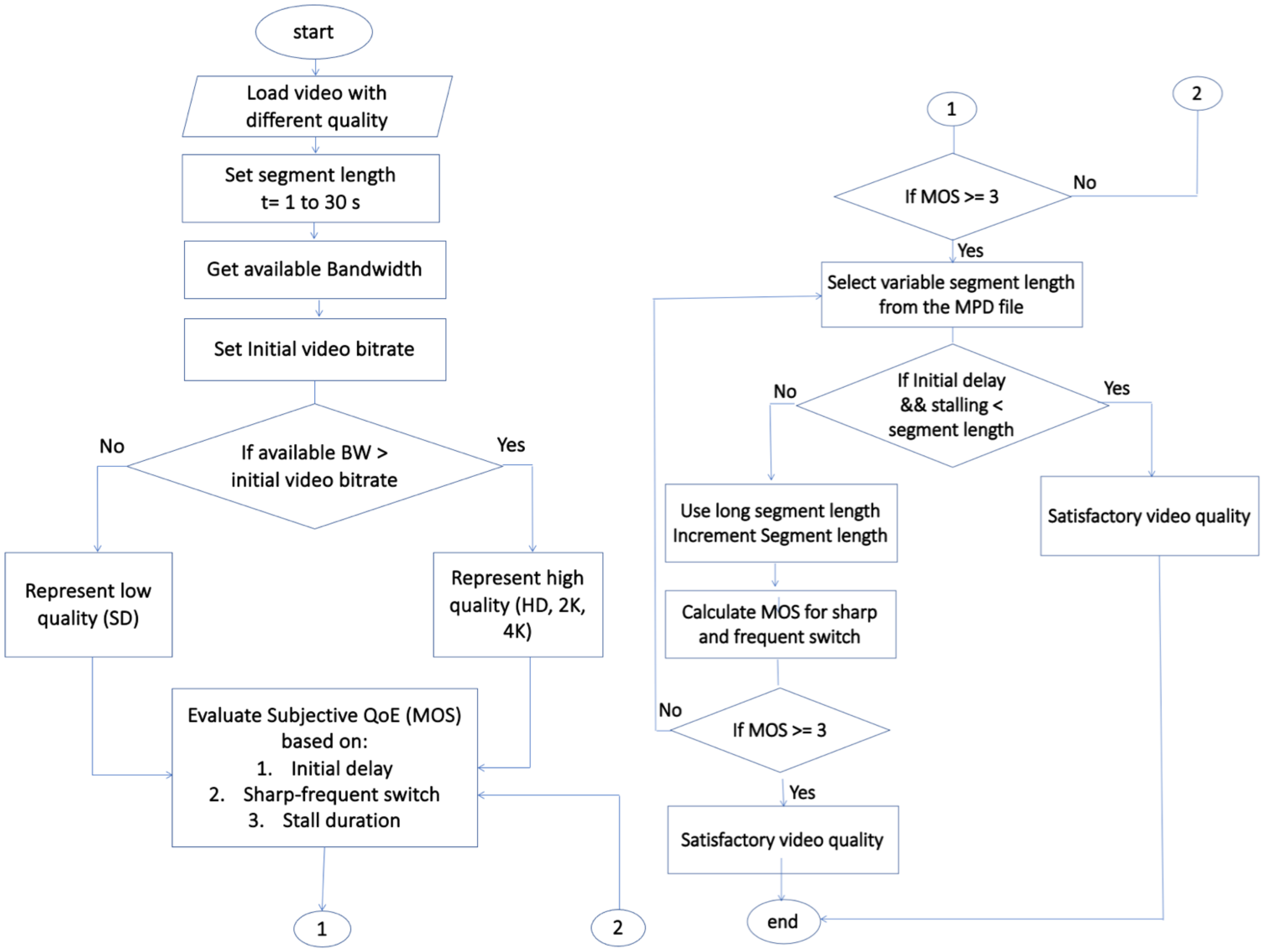


Fig. 7. Flowchart of the automated model.

6. Experiment for objective assessment

We have developed a new QoE model motivated by the analytical and observational results provided in Subsection 4.1.2. It considers video presentation quality and the impact of initial delay, number stalling, and GOP size events since objective assessments are quite complex for adaptive video streaming. The video content is available with different quality and comparison objective assessment between the original video and the delivered video is hard. The client-side may be rendered the video with different qualities. The extraction of several qualities from the same video is neither easy nor accurate because its chunks are decoded has different bitrate and different property during the playback time. Towards an objective assessment, the objective metrics for each quality of the video must be described in its preparation and according to the case study. Each video prepared for adaptive streaming includes a brief profile with its information, e.g., buffer length, time, representation quality, bitrate, and resolution, as shown in Table 5.

According to Figure 8, in order to provide the QoE objective assessment, we consider a method to evaluate the objective approach. The approach precedes the objective evaluation for each representation of the adaptive video. A network profile selected provides maximum availability of the network behavior where the rate of the loss equals zero. Therefore, the same sequences of the previous experiment were used in the objective QoE evaluation, as shown in Table 5. Three important metrics, namely PSNR, SSIM, and VQM were selected for HTTP adaptive streaming [39].

As displayed in Figure 8, according to Table 5, only the SSIM objective metrics can be found for the representations of the same video. We aimed to find a merely effective no-reference image quality assessment algorithm since in no-reference algorithms, the metric can speed the development process of real-time video QoE monitoring and estimation.

Therefore, the objective quality score can be embedded in the manifest file that describes the specifications of the video. The result is labeled with the MPD file of the adaptive streaming application. The manifest (XML file), or metadata file, is received by the client-side such that video information is available to the client, who reads the file with information on the objective metrics and requests the segments (GOPs) of video quality.

MPEG-DASH is commonly used as a streaming protocol. The GOPs series arrive at the client-side at the beginning of the process; their frames are decoded and sent for rendering, and then other series are requested and placed in the buffer for rendering. Viewers can visualize the last encoded frames due to the stalling interval.

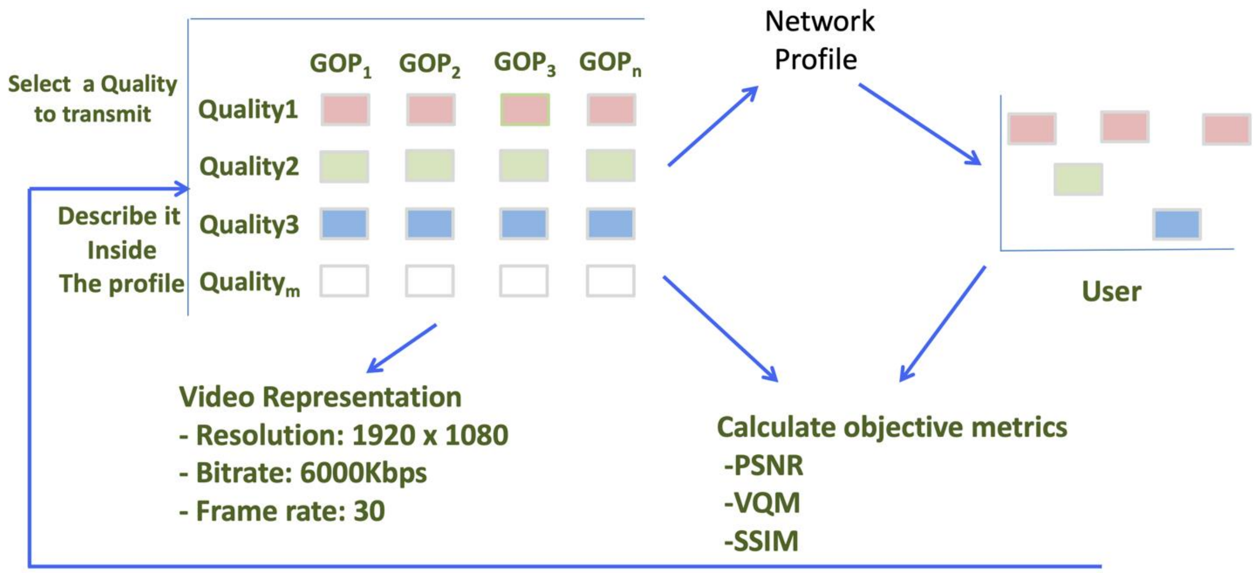


Fig. 8. Method of objective evaluation.

Table 5. Evaluation of objective-based on SSIM.

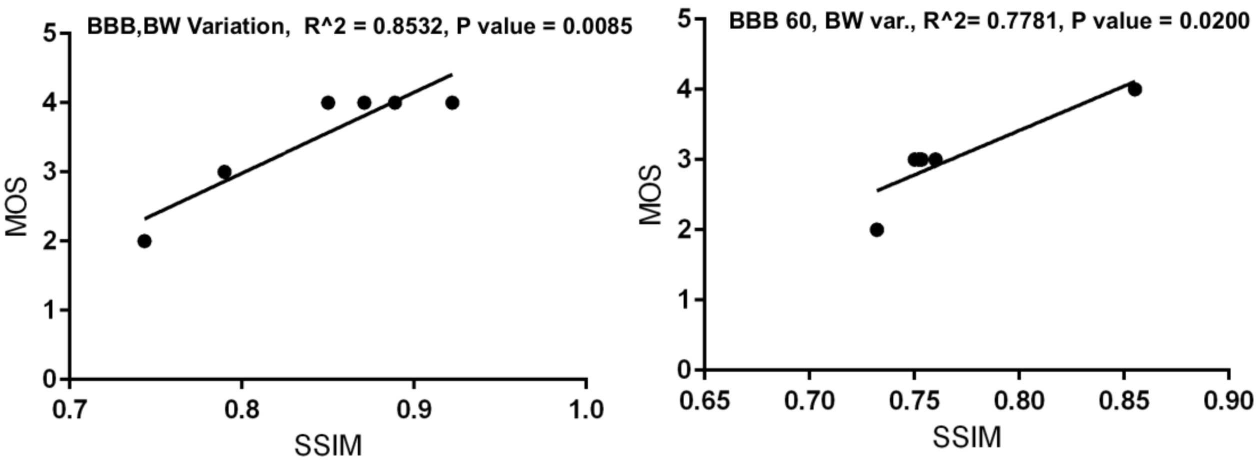
Quality level code	**Resolution**	**Bitrate (Kbps)**	**SSIM**
1	384 x 288	300	0.94539
2	512 x 384	700	0.97214
3	1280 x 720	1500	0.97658
4	1920 x 1080	6000	0.97898
5	2048 x 1440	11658	0.98567
6	3840 x 2160	19684	0.98768

7. Correlations between QoS and subjective and objective QoE

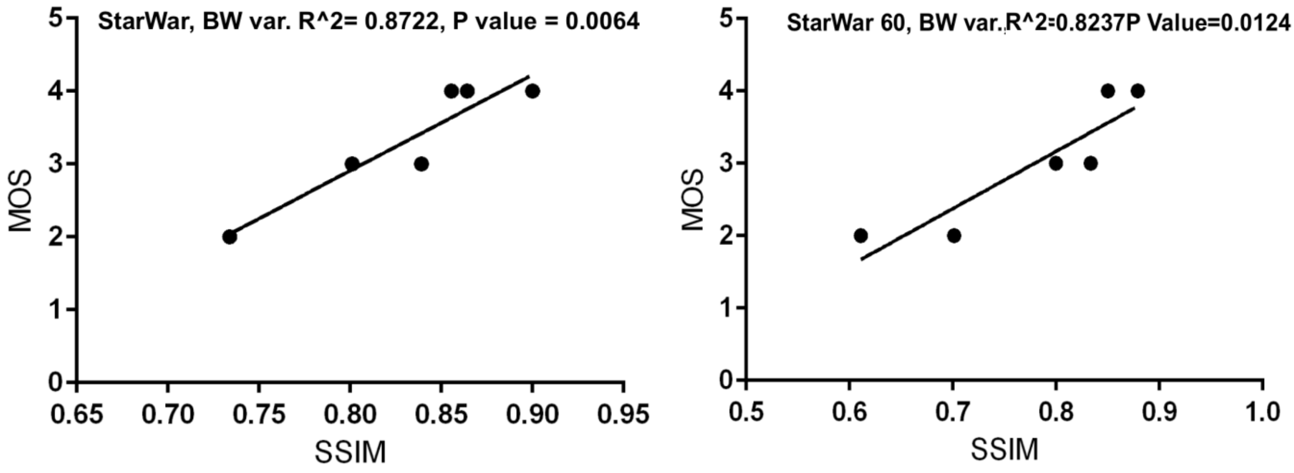
Pearson correlation coefficient, which aims to map subjective and objective QoE with the impact of QoS parameters, is obtained for the determination of the strength and direction of a relationship between QoS and subjective and objective QoE. A huge dataset is provided for the prediction of QoE in HTTP adaptive streaming and a python script finds the R and P values. P represents the measure of plausibility of the result, whereas R denotes a linear correlation between the attributes. According to both cases studied in previous sections, the proposed method decides on the evaluation of the QoE. As depicted in Figures 9, 10, 11, and 12, R and P values are found for subjective and objective, and the correlation between them are taken a closer look and the variation of the parameters of the QoS (Bandwidth, delay, and packet loss) is highly changing the results.

Our model employed the Pearson correlation equation for finding a correlation between MOS and SSIM metrics for different parameters of QoS (bandwidth, delay, and packet loss), as illustrated in Figures 9 through 12. Figure 9 displays the correlation between subjective (MOS) and objective (SSIM) metrics, which is significant when the frame rate is 30 fps, P = 0.0085, and R2=0.85 for a variable bandwidth. According to Figure 10, the correlation provides an optimal result for a delay variation when the frame rate is 30 fps, P = 0.010, and R2 = 0.83. Another test conducted (see Figure 11) evidenced the packet loss variation increases R2 and decreases P, thus leading to a higher correlation between MOS and SSIM. Finally, the effect of all parameters (bandwidth, delay, and packet loss) together was studied and is shown in Figure 12. The correlation results considerably changed for P < 0.0001 and R= 0.80 for BigBuckBunny sequence with 30 fps.

Altogether, a summary of the QoE modeling methodologies is given in Table 6, which highlights the methodology used, the sampling method, type of QoS, and QoE metrics. The comparison was performed with recent related studies [2;19;20;44;45;46;47;48].

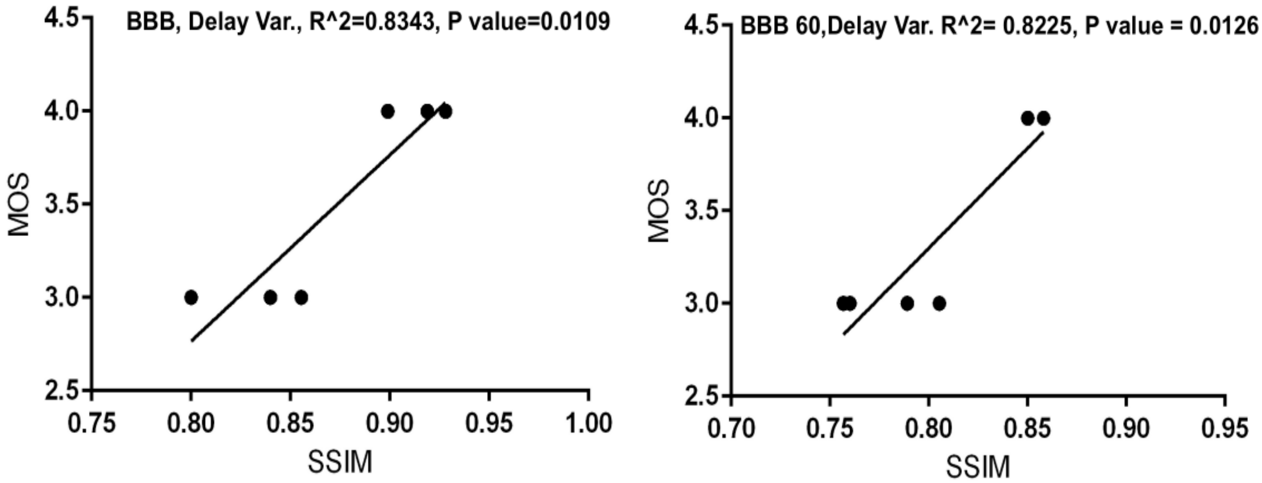


a) BigBuckBunny sequence.

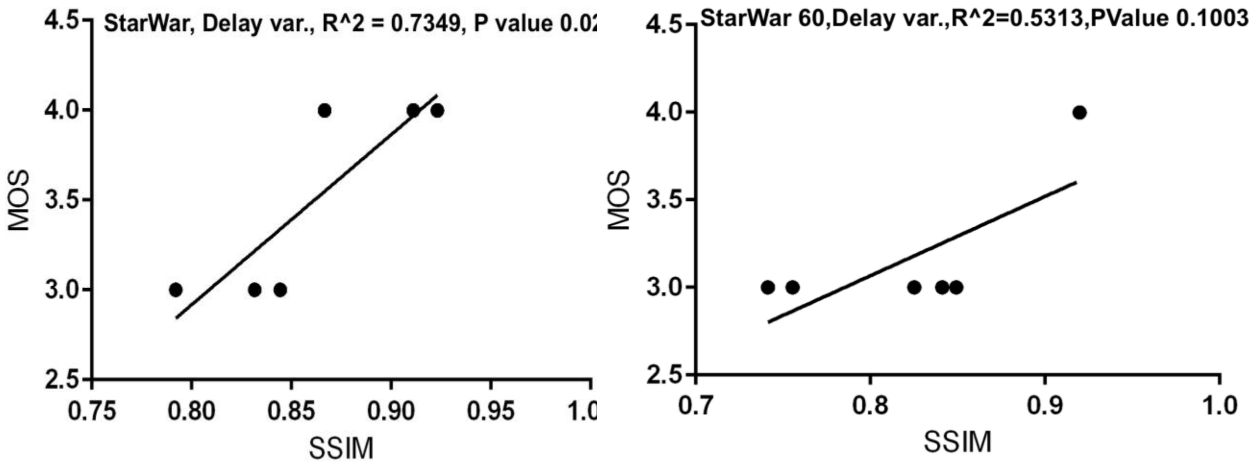


b) Star War sequence.

Fig. 9. Correlation when bandwidth has a high effect on the QoE (a and b).

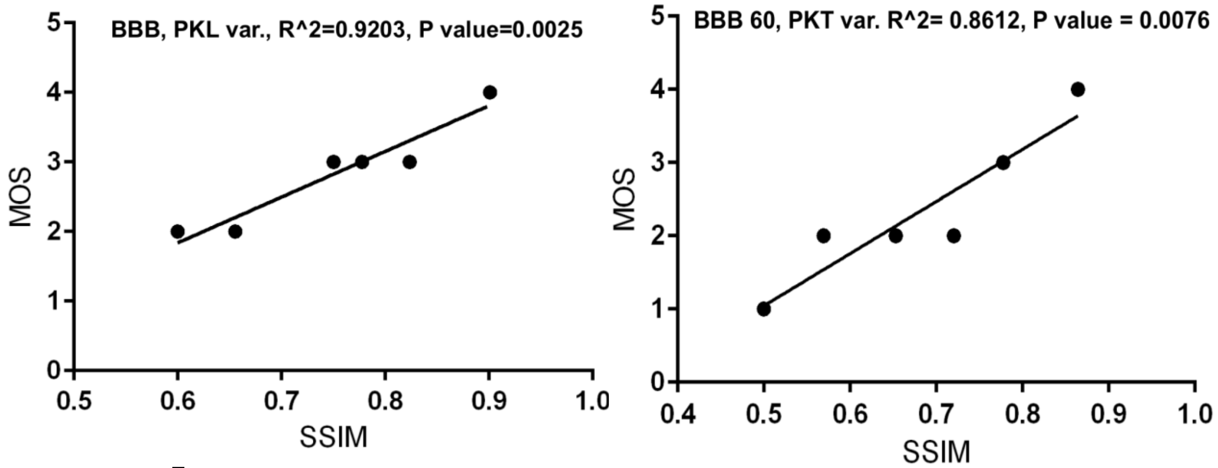


a) BigBuckBunny sequence.

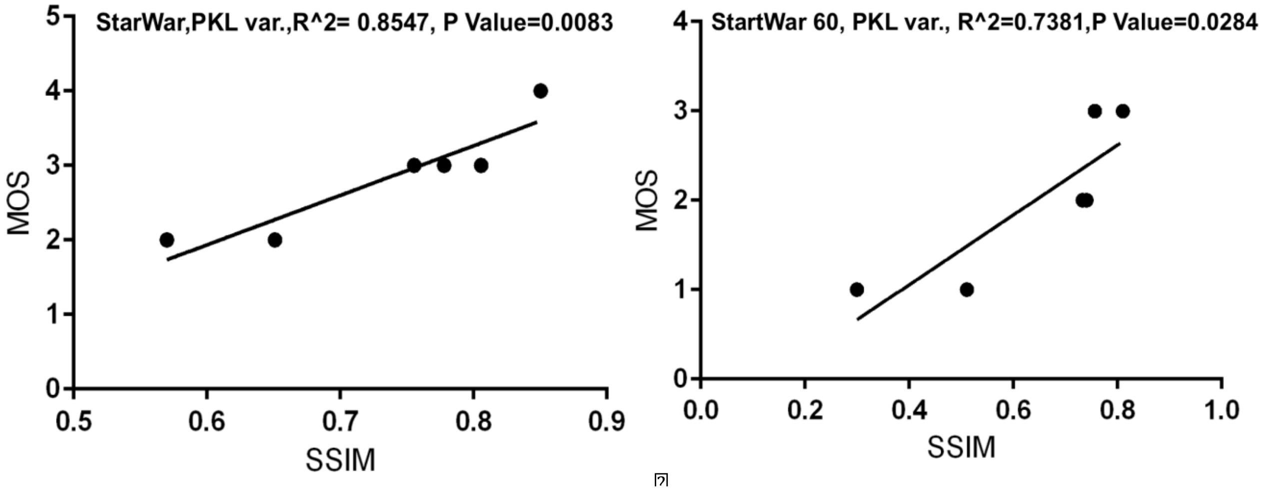


b) Star War sequence.

Fig. 10. Correlation when the delay has a high effect on the QoE (a and b).



a) BigBuckBunny sequence.
b)



c) Star War sequence.

Fig. 11. Correlation when packet loss has a high effect on the QoE (a and b).

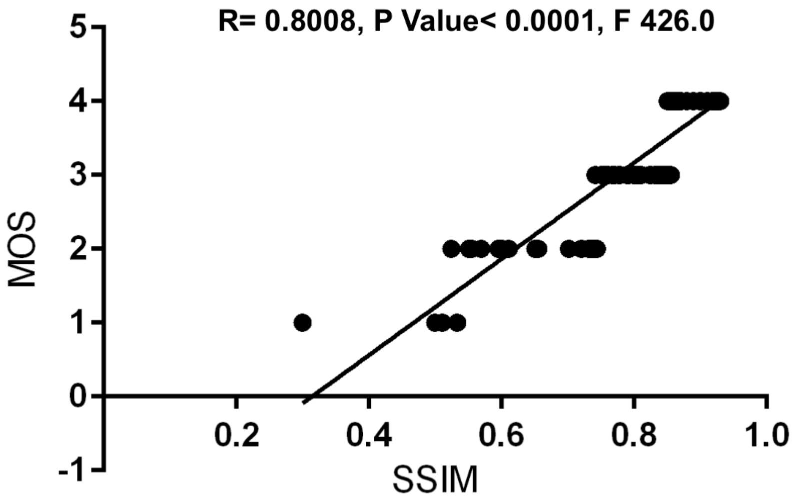


Fig. 12. The correlation is based on all parameters of QoS.

Table 6. Comparison of QoE methodologies of adaptive video streaming.

Ref.	QoE Methodology	Sampling method	Type of QoS parameter	QoE metrics	Model Limitation
[2]	Prediction from network QoS	Uniform	Bandwidth	Initial delay, buffer length, video stalls, switch frequency, MOS, CPU, and energy	Not based on automated model
[19]	Controlled Experimentation	Active learning	Bandwidth	Rebuffering events, quality switching, initial delay, encoding quality, and memory factors	Complex and not based on the learning model
[20]	Controlled Experimentation	Not applicable	Bandwidth	Throughput, quality switching, and video playout freezing	Lack of stability and weakness of performance
[44]	ITU-T P.1203 module algorithms	Not applicable	Bandwidth	Stalling metric	Not based on the learning model
[45]	Stream optimization	Not applicable	Bandwidth	SSIM, PSNR, and MOS	Not based on the correlation model
[46]	QoE-aware DASH system	Not applicable	Bandwidth	MOS	Not based on the correlation model

[47]	Controlled Experimentation	Uniform	Bandwidth	Startup delay, number of stalls, and video resolution	Longer time for training data and complexity
[48]	Data collected in the Wild	Not applicable	Bandwidth	buffer state, video state, and video resolution	High error-susceptibility and complexity
Proposed Model	Prediction from end user devices	Uniform	Bandwidth, Delay and packet loss	Video bitrate, initial delay, video stalls, switch frequency (Sharp and smooth), MOS, and SSIM	Not based on machine learning

Table 7 shows a comparison among our model and models regarding subjective (MOS) and objective (SSIM) quality measurements, and their correlation values. According to the results of our approach, SSIM is 0.9, the optimal MoS is 4, and the Pearson correlation coefficient is 0.92. Such values provide better results than those of the other approaches.

Table 7. Comparison among our approach and other models.

Related Models	**Optimal MOS**	**SSIM or RMSE**	**Correlation Algorithm**	**Correlation Value**
[2]	4	NA	NA	No
[31]	4	NA	Pearson correlation coefficient	High (P value: 0.9080)
[44]	4	RMSE: 0.333	Pearson correlation coefficient	High (P value: 0.892)
[50]	4	RMSE: 0.1277	Pearson correlation coefficient	High (P value: 0.9133)
Proposed approach	4	SSIM: 0.9	Pearson correlation coefficient	High (P value: 0.92)

NA Not Applicable

8. Conclusions and future work

This paper has reported an investigation of influence factors that affect the human visual QoE of adaptive video streaming over HTTP and proposed a method that evaluates QoE. The methodology is based on different observation metrics, such as segment length, initial delay, quality oscillation, and video stalls. Experiments conducted involved different sequences and subjective and objective metrics towards an accurate QoE evaluation. The subjective experiments revealed an interesting relationship between segment length and the impact of stalling, switching, and initial delay.

Therefore, the objective metrics were used in the evaluation, and the statistical model depicted the correlation between QoS and QoE and interaction between subjective and objective QoE. From the correlation approach, our method proved accurate for evaluating QoE of HTTP adaptive video streaming, and the restriction values of QoS parameters highly impacted the prediction of QoE. According to experimental results, QoS parameters are involved in the correlation outcome. The evaluation of QoE conducted by [2;12;28;40;41] was based only on throughput. However, On the other hand, our approach depends on three parameters (see Figures 9, 10, 11). The involved parameters for both subjective, objective evaluation, and QoS parameters provide an accurate correlation value R = 0.88 for all test strategies.

Our future studies aim the development of an automated model based on deep reinforcement learning with double Q-values towards end-users ' precise decisions, hence, a sophisticated scenario.

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